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Prediction of thermal sensation level in cold areas residential buildings using BP neural network coupling with improved particle swarm optimization algorithm

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Abstract. Thermal comfort reflects the subjective satisfaction of the person in the surrounding environment, and usually be appraised with thermal comfort vote. However, the environmental factors, such as air temperature, affect the thermal comfort. And, the air temperature changes with building envelope materials. Thus, the prediction of thermal comfort is a complex nonlinear problem. BP neural network can perfect fit the complex nonlinear model relation. But it have limited accuracy owing to their potential convergence to a local minimum and over-fitting. In order to improve the accuracy of prediction, an improved particle swarm optimization algorithm is proposed to optimize the optimization ability of particle swarm optimization algorithm. And using improved particle swarm optimization algorithm to optimize the initial weights and thresholds of BP neural network. The outputs of these findings demonstrate the proposed model has fast convergence speed and height prediction accuracy when it been applied to forecast the thermal comfort in indoor room.

Key words. Thermal comfort, Enclosure material, back propagation neural network, constriction factor PSO.

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1. Introduction

Thermal comfort researches can be called researches on human thermal sensation [1, 2]. Many scholars have carried out a large number of indoor experimental researches on thermal comfort [3, 4]. With the constantly deepening of thermal comfort field researches, it has been found that ASHRAE and PMV have low prediction accuracy [5]. Because there is [6] multilayer iterative non-linear mapping relationship between these factors, it is difficult to accurately predict human thermal comfort degree in different environmental condition. It is found through analysis and researches that BP neural network has strong self-learning ability and adaptability and it can approximate various forms of nonlinear mapping relationships [7], And it had been used by several authors [8–9]. Therefore, the neural network model can be used to predict human thermal comfort degree. Leopold Mba [11] and other people apply the artificial neural network to the forecast of air temperature and relative humidity of buildings in wet areas. The experimental results verify that the artificial neural network can be used to predict the influencing factors. Jörn Von Grabe [13] explores the potential of the artificial neural network to improve thermal sensation predictability by using the database of RP-884 adaptive model project. The results show that the designed neural network predicts the distribution of ASHRAE individual votes under the predetermined conditions and it outperforms the classical PMV index in predicting quality and information range.

The BP neural network model has some limitations, owing to their potential convergence to a local minimum and over-fitting. After comparing several algorithm [12], the combined model can improve the accuracy of result by complementing each other's advantages, but some of them need complicated cross mutation operation. The research of Leopold Mba [12], Jörn Von Grabe [13], and other people [14] are distributed in Cameroon and other places, but there is little literature that study on thermal comfort prediction in Asian Cold Region.

The paper puts forward an improved BP neural network method based on particle swarm optimization with contraction factors, to predict the indoor thermal comfort in cold area enclosure structure material environment in Subtropical monsoon climate zone of Xi'an, China. Firstly, using normalized method process the data, in order to speed up the gradient to find the optimal solution speed after the standardization and improve the accuracy. And then, using PSO algorithm fixed the problem that BP neural network assign initial weight and threshold with random way, and using construction factor particle swarm optimization further improved the BP neural network method. Focusing on the study that the data were used to analyze the root mean absolute error (RMSE) et al. of every model.

2. Experimental data

The data used to validate the CFPSO-BP neural network prediction model were from a Xi'an University. The experiment was carried out on the field of Xi'an, China, and the data of 1042 groups of metabolic rate, clothing resistance, temperature, humidity, black ball temperature and wind speed were collected. The data of body heat sensation was obtained by subjective questionnaire, and conducted actual application analysis. The table 1 show the parameters of the room outside the window, and the characteristics parameters of the staff:

Table 1. the parameters of the room outside the window, and the characteristics parameters of the staff

Category		Parameters
Outdoor window	Size	1.5 m × 1.5 m
	Material	Aluminum alloy emissivity < 0.25
		Air layer thickness 12 mm
	Heat transfer coefficient	$2.8\,\mathrm{W \cdot m^{-2} \cdot K^{-1}}$
	Transmittance	0.44
Indoor heat source	Staff heat dissipation	108 W
	Lighting power	$15\,\mathrm{W \cdot m^{-2}}$

Contents of the thermal questionnaire: (1) general thermal comfort right now et al.

Indoor objective measurement data and subjective survey questionnaire data obtained as shown in Figures 1 and 2.

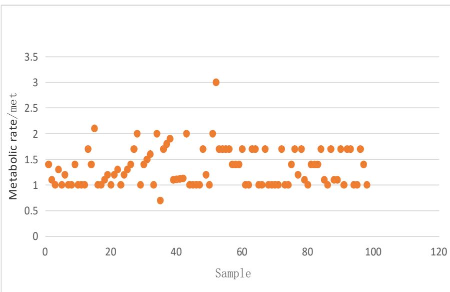

Fig. 1. Metabolic rate partial data

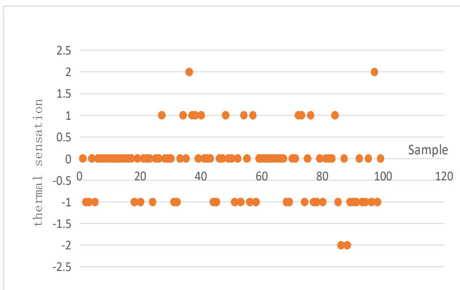

Fig. 2. Thermal sensation partial data

The autumn temperature in Xi'an in 2012 was between [15°C, 24°C], which belongs to the early autumn rainy season, and the temperature change is decreasing. The average precipitation during this period was 151.2 mm, which belongs to the rainy season and the percentage of humidity fluctuates up and down at 20%. The average radiation temperature changed little. The wind speed in the indoor environment was maintained between $[0, 0.2]$ m/s, and the environment was in general. Indoor metabolites were distributed in the distribution of [1, 2] between the staff in a relaxed state of sitting or standing mild activity. Clothing resistance in the [0.6, 1.3]clo, of which the first 30 samples concentrated in the 1clo, dress for the jacket, pantyhose and so on. After 70 samples of clothing thermal resistance was more dispersed, indicating that with the temperature drop, the different sensations among staffs were remarkable.

3. Method

3.1. Particle swarm optimization algorithm with constriction factors

1) Particle swarm optimization:

Using the particle swarm optimization to improve the neural network, there are simple strategy [15, 16] and less parameters that are needed to be adjusted, and without operations such as coding, cross and compilation in the genetic algorithm, the global optimum can be found by tracking the optimum value that is found currently. The learning optimization problems of the neural network have huge advantages with complex calculation, fast implementation speed [17] and high accuracy advantages.

2) Particle swarm optimization with constriction factors (CFPSO)

PSO algorithm does not actually control the speed of particles [18]. Clerc proposed the method of using the shrinkage factor χ, which describes a method to select the values of ω, c_1, and c_2 to ensure that the particle optimization algorithm converges, and by appropriately selecting these parameters, the boundary limit to the velocity can be eliminated and the insufficient search caused by the improper speed boundary settings can be avoided [19]. The velocity updating formula of particles becomes:

$$v_{i,j}(k+1) = \chi\{v_{i,j}(k) + c_1 r_1 [p_{i,j(k)} - x_{i,j}(k)] + c_2 r_2 [p_{g,j}(k) - x_{i,j}(k)]\}\,, \quad (1)$$

$$\chi = \frac{2}{|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|}, \varphi = c_1 + c_2, \varphi > 4\,. \quad (2)$$

3.2. Construction factor PSO-BP neural network structure

The structure of neural network represents Figure 3.

Algorithm design as follows:

Part1: sample data and normalization of sample data and

Part2: Initialization of BP neural network parameters

Part3: CFPSO optimizes initial weights

Step1: randomly initialize the positions and velocities of particles (population size is m) in a population;

Step2: evaluate the fitness of each particle;

Step3: for each particle, compare its fitness to its experienced best location pbest, if it is better, take it as the current best position pbest;

Step4: for each particle, compare its fitness to its experienced best location pbest of the whole part, if it is better, take it as the current best position pbest;

Step5: update the speed and position of each particle;

Step6: check whether a default maximum algebraic Gmax is reached; if satisfied, then output gbest and its target value and stop the algorithm; otherwise, turn to Step2.

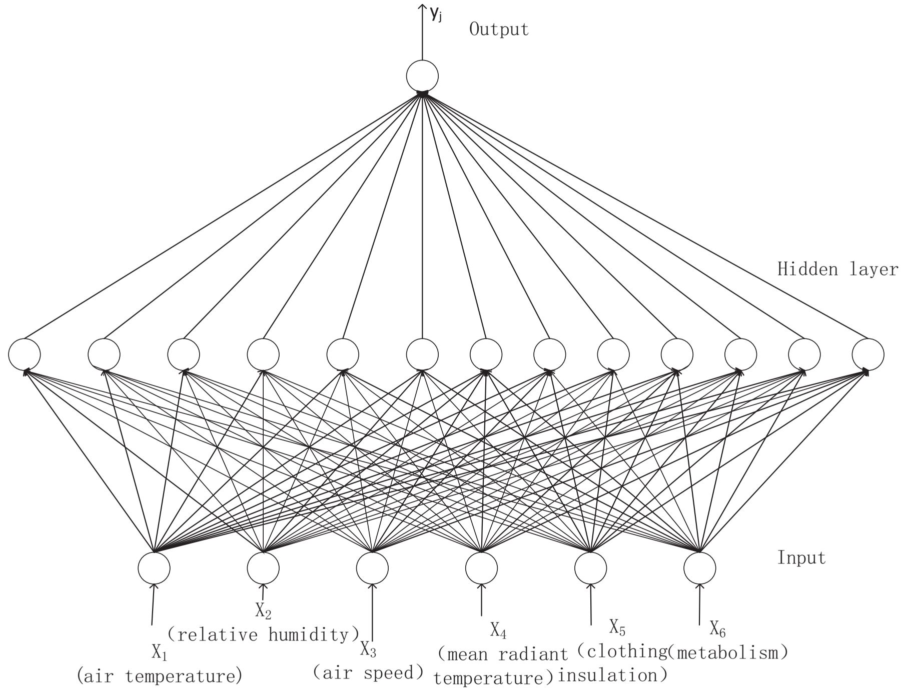

Fig. 3. Structure of thermal comfort prediction neural network

Part4: using the optimized neural network for prediction

Step1: get the initial weights and thresholds of the best neurons

Step2: error calculation

Step3: weights and threshold updates

Part5: verify model accuracy

The algorithm flow chart is shown in Figure 4.

3.3. Data preprocessing and model validation [20]

In this study, data are normalized by max-min standardization method formula (3), and the model performances are characterized by the root mean square error ($RMSE$), the mean absolute error (MAE) and the coefficient of correlation (R). $RMSE$, MAE and R can be evaluated as:

$$x_i = \frac{x_i - x_{mid}}{\frac{1}{2}\left(x_{\max} - x_{\min}\right)} . \tag{3}$$

The x_i represents the input or output data, and x_{mid} represents the intermediate value within the changing range of data, and $x_{\max}$ represents the maximum value of the changing range of data, $x_{\min}$ represents the minimum value of the changing range of data.

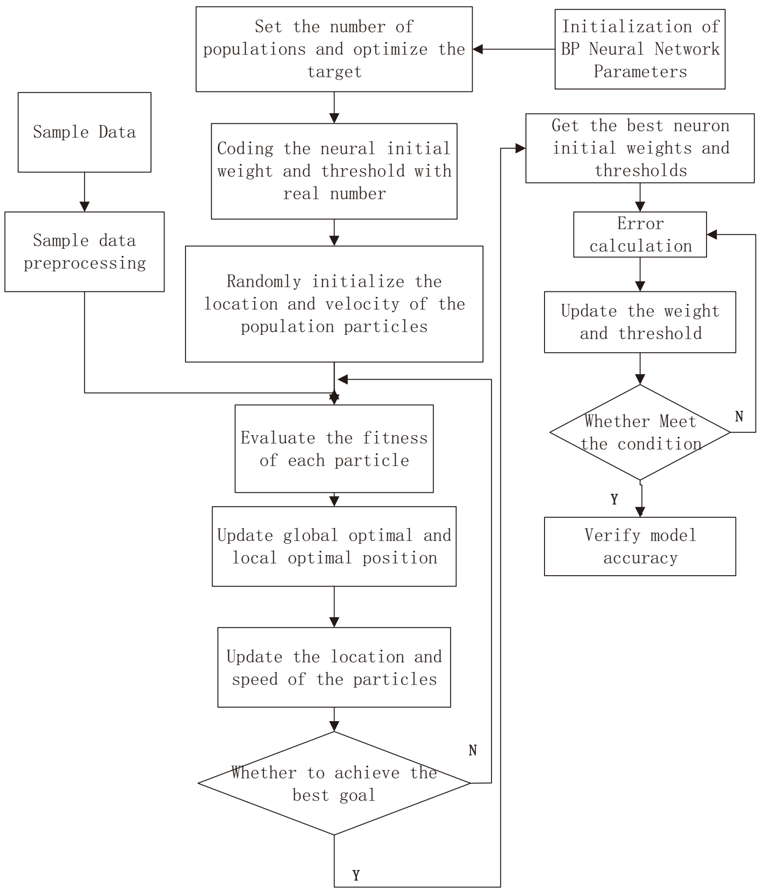

Fig. 4. CFPSO algorithm for hermal sensation prediction

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|E_i| = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i|\,, \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}E_i^2} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \widehat{X}_i)^2}\,, \tag{5}$$

$$R = \frac{\sum\limits_{i=1}^{N}(P_i - \bar{P})(O_i - \bar{O})}{\sqrt{\sum\limits_{i=1}^{N}(P_i - \bar{P})^2 \sum\limits_{i=1}^{N}(O_i - \bar{O})^2}}\,. \tag{6}$$

P is the actual output, O is the expected output.

4. Result and discussion

The data used to validate network prediction model were from a Xi'an University. The experiment was carried out on the field of Xi'an, China, and the data of 1042 groups of metabolic rate, clothing resistance, temperature, humidity, black ball temperature, wind speed were collected and body heat sensation. The study used 942 data sets as training samples and 100 data sets as test samples. After normalized processing with formula (3), each group uses body heat sensation to be expected output, other influencing factors to be input. The parameters BP neural network structure are set 13 hidden layer, trainlm training function and 0.05 learning rate, according to experiments result in Table 2, Table 3. The parameters of the PSO-BP network are set as:

$c_1 = c_2$ — Learning factor/acceleration factor is 2.05;
$[V_{\min}, V_{\max}]$ — The velocity range of the particle is set to $[-1, 1]$;
I — Evolutionary algebra is set to 100;
$Sizepop$ — Swarm size set to 30;
ω — The inertia weight is set to 0.5;
$G_{\max}$ — The maximum number of evolution is set to 100;
$Pop\max$ — The maximum population area is set to 5;
$Pop\min$ — The minimum value of the population area is set to -5;

The network include 78 weights from input layer to the hidden layer, and there are 13 weights from the hidden layer to the output layer. The optimal initial weights obtained by the PSO-BP algorithm are shown in Table 5.

The parameters of the construction factors optimization BP algorithm are set as follows:

$c_1 = c_2$ — Learning factor/acceleration factor is 2.05;
χ — Contraction factor is set to 0.729 according to formula (1);

Table 2. Comparison of five improved algorithm predictions

Training function	Number of neurons	RMSE	MAE	Correlation coefficient	TIME/S	EPOCH
traingd	7	0.2833	0.6100	0.43337	36	1000
	13	0.2662	0.5700		35	1000
traingdm	7	0.6607	1.1700	0.42831	1	15
	13	0.6010	0.8500		1	12
traingdx	7	0.3550	0.6100	0.27285	3	16
	13	0.2818	0.4800		2	67
trainlm	7	0.2544	0.5200	0.52971	1	25
	13	0.2477	0.4200		1	22
trainbfg	7	0.2680	0.4400	0.13677	2	26
	13	0.2604	0.5400		1	16

Table 3. Four different learning rate

Learning rate	RMSE	MAE	EPOCH
0.1	0.2421	0.5500	17
0.05	0.2381	0.4900	15
0.02	0.2390	0.4500	14
0.01	0.2477	0.4200	14

Table 4. Optimal initial weight table from hidden layer to ouput layer

1	2	3	5	6
−1.9189	−0.3660	−2.0304	−0.1246	1.3160
2.1806	−1.8074	3.2791	2.6945	1.1495
−0.2624				

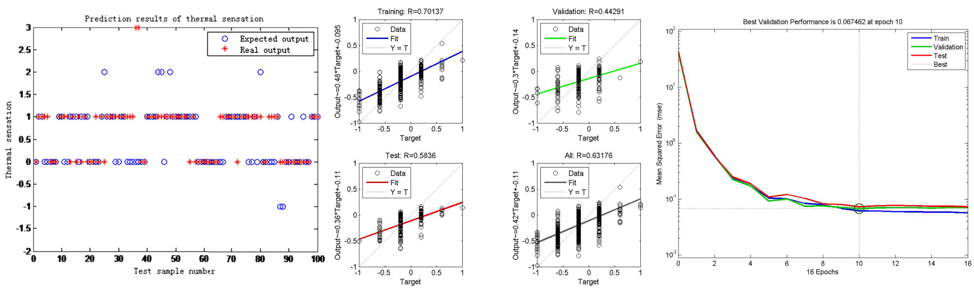

Fig. 5. Particle swarm algorithm modified the weight of BP network

Figure 5 presents the result of correlation coefficient between the actual output and the expected output. The results becomes 0.63176 after using the particle swarm optimization algorithm, which indicates that the actual output is most closely related to the expected output and the training effect of the network is better. And the table 5 represents the comparison between BP neural network and PSO-BP neural network.

Table 5. The correlation coefficient between two neural networks

Neural networks	Correlation coefficient
BP	0.52971
PSO-BP	0.63176

From the table6, the PSO-BP neural network with construction factor converges faster than the PSO-BP network.

Table 6. Accuracy of Different Neural Network

Neural network	RMSE	MAE	EPOCH
BP	0.2581	0.7702	263
PSO-BP	0.2042	0.4017	16
CFPSO-BP	0.1965	0.4108	11

From the predicted results in the Table 6, we can see that these neural networks can predict human thermal comfort according to the factors that affect the thermal comfort. From the RMSE and MAE in the Table 6, it can be seen that the prediction accuracy and adaptability of the PSO-BP network and CFPSO-BP network are enhanced for one time, because PSO can find the global optimal value by tracking the optimal value that is found currently, and the neural network learning optimization problems with complex calculation have great advantage; therefore, there are fast realization speed and high precision. However, the CFPSO-BP algorithm achieves the way of controlling the speed range with shrinkage factors, and the velocity range of particles that are not needed to set is $[V_{\min}, V_{\max}]$, which avoids that the value is too high to pass through the best solution and the value is too small to sufficiently search space; therefore, the prediction accuracy and adaptability of the network can be further enhanced.

5. Conclusion

In this paper, a network model for indoor thermal comfort index prediction in cold area envelope material housing is established, and a CFPSO-BP neural network model with improved initial weight is proposed by using particle swarm optimization with shrinkage factor to predict indoor thermal comfort. Finally, with the qualitative analysis, compare the prediction effect of the application of CFPSO-BP neural network, BP neural network and PSO-BP neural network to predict the thermal comfort index. Through examining with the measured data in October, 2012–June, 2015 in Xi'an, the result show that the proposed CFPSO-BP method can effectively solve the problem that the BP neural network is easily converged to the local minimum and the accuracy is limited in the thermal comfort prediction. At the same time, the CFPSO can solve the problem that the standard PSO cannot control the speed range, to speed up the network forecast speed. Therefore, CFPSO-BP neural network is superior to the existing BP neural network method in indoor thermal comfort index prediction.

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